A Computer-Based Incentivized Food Basket Choice Tool: Presentation and Evaluation

Jonathan Spiteri, Jonathan James, Michele Belot

No. 69 /18

BATH ECONOMICS RESEARCH PAPERS

Department of Economics

A Computer-Based Incentivized Food Basket Choice Tool - Presentation and Evaluation*

Jonathan Spiteri[1], Jonathan James[2], and Michèle Belot[3]

[1]Department of Economics, University of Malta

[2]Department of Economics, University of Bath

[3]European University Institute

January 17, 2018

Abstract

We present and evaluate a new incentive-based tool to measure people's dietary choices in a low-cost and time effective manner. Respondents are asked to allocate a fixed monetary budget across a choice of around a hundred grocery items with the prospect of receiving these items with some probability delivered to their home by a real supermarket. The tool has the advantage of offering a broad coverage of dietary choices, allows inference of macro-nutrients and calorie, and allows the researcher to fix the choice set participants can choose from. We compare the information derived from our incentivized tool, and compare it to alternative low-cost ways of measuring dietary intake, namely the food frequency questionnaire and a one-shot version of the 24-hour dietary recall, which are both based on self-reports. We invited 255 low income participants to our laboratory and collected measures using these three alternative tools. We compare the calorie intake indicators derived from each tool with a number of biometric measures for each subject, namely weight, body-mass-index (BMI) and waist size. The results show that the dietary information collected is only weakly correlated across the three tools. We also find that only the calorie intake measure from our incentivized tool is positively and significantly related to each of these biometric indicators. By contrast, we find no significant correlations for either of the two measures based on self-reports. We therefore argue that our tool may be useful for research conducted with limited time and budget.

*This project is funded by the European Union's Seventh Framework Programme, under grant agreement no. 607310.

JEL Classification: C81; C83; I12; I18.

Keywords: Incentives; Nutrition; Dietary Measures; Laboratory Experiments.

1 Introduction

Academic interest in nutrition has increased dramatically in recent years and across a variety of disciplines spanning Social and Medical sciences. One of the major challenges encountered by researchers and practitioners across all disciplines is related to the measurement of dietary intake among people. This challenge is important to tackle because a proper measurement of dietary intake is crucial to the design and evaluation of policy interventions. There exist a variety of tools that have been evaluated and validated, going from simple surveys to more sophisticated methods like the 24-hour dietary recall Beaton (1979), a questionnaire-based tool whereby subjects are asked to provide details regarding all food and drink items consumed within the last 24 hours, including portion size, brand, side-dishes, sauces, snacks and condiments. These recalls can be either administered by qualified nutritionists or self-administered, and are considered to be the gold standard for nutrition-based studies. The major benefit from such methods is that they target actual dietary intake. However, the reliability of this tool depends on memory accuracy and truthful reports. It also sometimes requires having multiple entries for each person over several days, in order to obtain a truer picture of the subject's actual diet, thereby making such measures somewhat costly. In addition, the problems associated with self-reported data are particularly acute for dietary recalls since research has shown that people who are either obese or at risk of obesity are more likely to under-report their true dietary intake, which may limit the reliability of any results obtained (Lichtman et al., 1992).

On the other side of the spectrum, we find methods that are based on purchases rather than actual intake, such as those using scanner data (such as Griffith and O'Connell (2009), Griffith et al. (2015) and Griffith and O'Connell (2010)). The difficulty here is that there might be a discrepancy between purchase and consumption behavior, and it is more difficult to separate individual consumption from household consumption.

This paper contributes towards this methodological debate by proposing a new incentivized method of information elicitation which can be administered relatively inexpensively either in a laboratory or online setting. In essence, the idea behind our proposed approach is to incentivize respondents to provide accurate responses, building on the substantial existing literature on real choice experiments across several fields, including nutrition (e.g. Adamowicz et al., 1998; Carlsson et al., 2007). Our approach fits in spirit with the approach of recent studies that experimentally evaluate the effects of interventions on dietary choices by looking at a limited set of choices like lunch or snack choices (e.g. Bollinger et al., 2011; Lynch Jr and Zauberman, 2006). These choices are obviously not a reflection of the entire spectrum of dietary choices across an entire day. Indeed, it may be the case that any healthy choices or calorie reductions recorded in terms of meal choices may be compensated by increased consumption of unhealthy or higher-calorific options in another meal, as partially observed in Wisdom et al. (2010). The idea here is to collect information about food purchases in a low-cost and efficient way.

The tool we proposed is inspired by current and common online supermarket interfaces. As part of this tool, subjects are allocated a fixed budget and asked to select among a range of around a hundred food and drink items typically found at a local supermarket such as fruit and vegetables or ready meals. The range has been selected from real on-line supermarket items and includes popular items. Participants are incentivized to make 'honest' choices by having a chance of receiving their basket at home. All choices are recorded, with the tool also containing individualized nutritional data for each food and drink item available from the online supermarket, including calorie content, fats and sugar, thus allowing the researcher to calculate the nutritional composition of each subject's choices.

One important feature of the tool is that it allows researchers to determine the food choice set. That is, researchers can determine what foods people can choose from. This is potentially useful because there is a concern that dietary choices may be limited by supply - the idea that food deserts exist and make it hard for certain groups of the population to access certain foods, such as fresh fruit and vegetables. With this tool, one can fix the choice set and study the demand conditional on this choice set.

To evaluate the usability and functionality of our proposed food choice tool, we invited low income individuals (n=255) to our laboratory. Our focus on low income individuals stems from the well documented socio-economic gradient in chronic diseases (Dalstra et al., 2005). We are interested in comparing the information obtained with alternative ways one could collect information with limited time constraints and budgets. We also collected information using two alternative measures of dietary intake, namely a Food Frequency Questionnaire (FFQ), a one-shot version of a self-administered 24-hour dietary recall. We first compare the nutritional profiles of each subject across the three tools to assess whether the results obtained are similar to one another. Secondly, we correlate the total calorie intake derived from each of the three dietary measures with a number of subject-specific biometric measures, weight, body-mass index (BMI) and waist size, all of which have a well-documented relationship with dietary intake (Newby et al., 2003).

Overall, we find that the measures are not strongly correlated. We find no significant relationship between the calorie, fat and saturated fat intakes inferred from the three methods. When comparing the nutrient content inferred from each tool with the biometric measures, the only statistically-significant and positive results obtained are for the calorific intake measures obtained via our food choice tool. By contrast, we do not find any statistically-significant relationship between calorie intake measures from the FFQ or 24-hour dietary recall and our various biometric measurements. This lack of correlation may be due to a systematic bias in the reported levels of calorific intake by participants (similar to that suggested in Macdiarmid and Blundell (1998)) and a predominance of noisy observations which would raise standard errors and thus suppress significance levels.

Our incentivized food choice tool has a number of important advantages. First, it provides a quick and relatively inexpensive way of capturing people's dietary choices, without having to repeatedly administer a survey in order to obtain multiple data points. This is particularly important in field work where multiple surveys may be both infeasible and prohibitively costly. Second, the online supermarket-based interface allows for a much broader array of food and drink items to be selected, encompassing all main meals and snacks for up to an entire week (depending on the budget allocated), thereby providing a more complete and representative record of the participants' typical purchasing behavior. Third, by incentivizing participant responses by delivering the food and drink choices for all or a selection of participants, the tool can help to circumvent any issues associated with inaccuracies and under-reporting prevalent in self-reported survey measures (Podsakoff and Organ, 1986). Fourth and as already mentioned, it allows researchers to fix the choice set.

2 Related Literature

This paper contributes to the growing literature on the use and development of various measures of dietary choices. The nutrition and epidemiology literature has proposed several tools which could be utilized in order to gauge people's diets. The 24-hour dietary recall is perhaps the most widely-used method of eliciting intake patterns by nutritionists and epidemiologists (Johnson, 2002), particularly since people's memory of what they actually consumed may be more precise, although as pointed out by Block et al. (1982) the variability of intake from day to day may hamper the representativeness of one-day recalls. Another popular method for eliciting dietary patterns is the Food Frequency Questionnaire (FFQ), which typically asks respondents to indicate the frequency with which they have consumed a fixed list of food and drink items over the past month (Cade et al., 2004). The benefits of using the FFQ are largely based around its practicality as well as its ability to minimize day-to-day variation in diet since it is nominally a one-shot measure (Kristal et al., 1992), although doubts regarding its accuracy have been widely-cited in the literature due to the closed-nature of the questions asked and the possibility of errors or under-reporting (Resnicow et al., 2000). Several other methods have also been proposed, like dietary food logs and diet history, each with their own pros and cons, although the pervasiveness of the aforementioned two methods remains Shim et al. (2014).

By contrast, our proposed food choice tool seeks to elicit dietary choices by incentivizing them. Previous work in the literature has also sought to utilize revealed preferences in order to derive information regarding people's dietary choices. For example, Griffith and O'Connell (2009), Griffith et al. (2015) and Griffith and O'Connell (2010) all make use of highly-detailed panel data based on consumers' scanned supermarket purchases in order to obtain estimates of household dietary choices across a variety of nutrients and food categories, while controlling for prices. In addition, several experiments (both in the lab and in the field) have relied on incentivized or real-world choices (Kozup et al., 2003; Elbel et al., 2009;

McFerran et al., 2010).

In particular, our paper is closely-related to the branch of the sizeable literature of *real choice experiments* (RCEs) in the context of dietary choices (Chang et al., 2009; List and Gallet, 2001; Loomis et al., 2009). For example, Lusk and Schroeder (2004) use a randomized choice experiment in order to assess participants' willingness to pay for five different types of quarter-pounder steaks of varying quality and characteristics, while Alfnes et al. (2006) used similar methods in order to elicit preferences regarding the color of salmon. Our paper builds on these ideas by developing a unified, intuitive tool to assess dietary choices, where the setting is familiar and choices are realizable, thereby incentivizing true responses. This tool can be utilized in a variety of settings, from lab and field experiments to online administration, and represents a relatively inexpensive way of eliciting choices when compared to other tools like the 24 hour dietary recall.

Our paper also contributes to the well-established literature on survey design and information elicitation techniques. The fundamental driving force behind the emergence of this literature is the skepticism surrounding self-reported responses (e.g. Gonyea, 2005). In fact, various authors like Podsakoff and Organ (1986) have pointed out the significant potential drawbacks of relying on self-reported survey methods for data elicitation, including respondent inability to recall vital information, possible dissonance between respondent actions or beliefs and his/her self-image, leading to biased responses, and problems with understanding the questions asked.

This issue is particularly relevant since, as pointed out in Bertrand and Mullainathan (2001), response errors or omissions are typically correlated with key individual characteristics and behavioral tendencies, thus potentially introducing biases in any inferred results. Within this context, several alternative elicitation techniques for surveys have been proposed across several disciplines, including open-ended (as opposed to closed) questions and bidding games (Diener et al., 1998), randomized response techniques (Warner, 1965) and item count techniques (Raghavarao and Federer, 1979). The concept of our tool is based on revealed preferences, building on the theoretical underpinnings provided in Berg et al. (2010) regarding the ability of material incentives to generate economically-consistent and truthful behavior.

3 The Food Choice Tool

The incentivized information-elicitation method developed in this paper is a computer-based food choice tool. As discussed earlier, the aim of this tool is to elicit reliable and accurate dietary patterns from respondents, which in turn can be used to evaluate the effectiveness or otherwise of various interventions aimed at changing these behaviors. This tool has a simple user interface that is based on an online supermarket with a wide array of food and drink items that can be selected. The items are organized under six main headings (each represented by a separate tab at the bottom of the page): fruit and vegetables, meat and fish, bread and grains, confectionery and snacks, ready meals and drinks. The food and drinks have been selected as the most popular items in their respective categories as of March 2016 (the month of the tool's inception), as listed on one of the UK's leading supermarkets' official website. In total our food choice tool contains 120 different items; these are listed below in Table 1, while Table 2 provides the average nutrient content (per 100g) of each of the six food categories.

In the food choice tool, each item is listed along with a thumbnail picture and its price, which is the actual price as at March 2016 based on listings on the same leading supermarket's website, thereby ensuring that the prices reflect actual high street prices. The tool operates like a basic online supermarket, where respondents can select any food or drink item by specifying a quantity in the space provided next to each item. There are no restrictions on food choices, neither in terms of which items can be selected, nor in terms of the quantity of each item that can be picked. A number of screenshots of the tool, showing the various food and drink items on offer as well as the user interface, are shown in Figure 1.

The last tab/category shown in the tool is the 'Shopping Cart' page, which lists all of the items (and quantities) selected by the user, together with the total amount 'spent'. It is relatively straightforward to set a fixed budget that participants can spend; this should ideally reflect average household weekly or periodic spending at the supermarket in order to garner a more complete picture of participants' food intake. The system will then notify participants whenever this budget has been exceeded via a pop-up dialog box, inviting them to delete any items as appropriate. Once the participant is satisfied with the choices made, he/she can press a button at the bottom of the 'Shopping Cart' tab labeled 'Checkout' in order to save the choices and close the program. Note that if the pre-set budget has been exceeded, the system will not close down and instead notify the user to modify his/her selection.

Incentivizing the choices made is one of the main features of this tool, in order to avoid the pitfalls associated with self-reported or survey based information elicitation methods. The appeal of our food choice tool lies in the fact that incentives can be flexible and thus tailored to suit a variety of research budgets and logistical realities. The most straightforward and direct method would be to inform all users beforehand that their choices would be ordered from an actual supermarket and delivered to them within a few days, depending on their requirements. However, this may prove to be infeasible, both financially and logistically, as it requires ordering each basket and organizing food deliveries for each participant. Therefore, we propose an alternative solution whereby once all choices have been made, one or several participants are picked at random, with only their chosen baskets ordered and delivered. This randomized scheme mitigates against the problem of financial and logistical infeasibility. Moreover the literature on random lottery incentive systems in experimental economics shows that the choices made under this regime are not systematically different from those made under a full-pay system (Starmer and Sugden, 1991; Cubitt et al., 1998).

The food choice tool records all food and drink choices made by each user, both in terms of quantities and amounts spent per item/category. Crucially, the tool also contains detailed nutritional data for each of the 120 items listed, including information regarding total calorie content, total fats, saturated fats, carbohydrates, sugar, salt, protein and fibre, both as aggregates and also per 100g. Therefore, our proposed food choice tool can also measure the nutritional composition of each user's food choices, thereby providing a record of their individual dietary patterns. This tool provides clear benefits over other self-reported measures by incentivizing people's responses to ensure greater reliability of data, while also improving the representativeness of food choices due to its supermarket interface and budgetary allowance, meaning that selected baskets would reflect multiple meals as opposed to one-shot meals or snacks.

Although our proposed tool has various important benefits, there are important specific aspects, which may turn into shortcomings depending on the question one is interested in. First, our tool focuses on *planned* food expenditures rather than impulse purchases that yield immediate gratification, given that the winning basket would not be immediately delivered. A significant body of work has shown how these two types of food expenditure can differ (Stern, 1962; Kollat and Willett, 1967), and in particular how impulse purchases are associated with self-control failures and thus spending on unhealthy items (Baumeister, 2002; Thomas et al., 2011). Thus, it may be the case that the estimates of dietary intake obtained via our tool may under-represent the actual amount of unhealthy food consumed by respondents. Second, as with scanner data measures, it is not clear that this provides an accurate measure of consumption. Finally, the tool is does not necessarily capture individual behaviour, as we cannot enforce that individuals only purchase items for their own consumption.

In the version of the tool we propose here, participants do not have access to the nutritional information for any of the food and drink items; rather, the food choice tool only displayed a thumbnail image of each item, together with a short description and its price (in £). This design differs somewhat from the standard grocery shopping experience, both in-store and online, since typically consumers would have access to each product's nutritional information, and would be able to consult this information prior to making their purchasing decisions. We opted to omit such information in order to expedite the food selection process in the lab, thereby enabling a relatively quick collection of information. Furthermore, evidence suggests that people do not regularly read nutritional labels when purchasing their food and drink items from supermarkets, particularly when it comes to familiar and/or repeat purchases (e.g. Cowburn and Stockley, 2005; Graham and Jeffery, 2011). This said, it would be relatively simple to include nutritional or other relevant information in the tool if one would wish to do so.

4 Experimental Design

Having laid out the key aspects of our proposed tool, we now proceed to compare it to other leading tools used by nutritionists and epidemiologists. To this end, we ran a laboratory-based experiment whereby participants were asked to complete a food frequency questionnaire (FFQ), a 24-hour dietary recall, as well as our supermarket-based food choice tool. We then compare the measures of nutritional intake derived from each tool, and relate them to a number of biometric indicators namely body-mass index (BMI), weight and waist size.

The experiment was part of a wider study on health and nutrition, which was held at the Behavioural Laboratory at the University of Edinburgh (BLUE). Briefly, the initial wave of the study, which ran in June 2016, focused on the impact of different types of health information, as well as time availability, on food choices. As described in a different paper (Belot et al., 2016) we sought to compare the impact on dietary choices resulting from the provision of no health information (our control group), the provision of generic health information on heart disease and diabetes, derived from the UK's National Health Service (NHS) and Harvard Medical School, as well as the provision of tailored health information group, who were asked to undertake a computer-based health assessment that provided personalized information regarding their individual risk of contracting heart disease and diabetes relative to the average person their age and gender living in Scotland. Note that in this study, the measure of dietary choices used was derived from our incentivized food choice tool, which was completed following the health information stage. In addition, we also looked at how varying the time available for participants to make their food and drink choices from our food choice tool influenced the nutritional composition of their choices.

The second wave of the study, which is relevant to this paper, ran from Monday 12th to Friday 16th September 2016, and was also held at the BLUE lab. Each day consisted of four time slots: 9.30am-11am, 11.30am - 1pm, 2.30pm - 4pm, 5.30pm - 7pm, and participants were able to indicate their preferred time slot(s) beforehand. We conducted the experiment in 20 identical sessions of up to 18 individuals per session, spread over 5 consecutive days. Participants had received an information leaflet in advance at their home address as part of the wider study, which kicked-off in June 2016, and which also contained some information regarding this phase of the study, as well as a consent form. All procedures were done in accordance with the ethical guidelines established by BLUE and the University of Edinburgh's School of Economics, and the study was granted full ethical approval beforehand.

4.1 Sample and Recruitment Procedure

The sample for our experiment consisted of 255 participants from low-income backgrounds ($<$ £26,500 annual income) living in the surrounding precincts of the University of Edinburgh's main campus. More specifically, participants had to satisfy the following eligibility criteria:

- Must be over 18 years of age;

- Must live in Edinburgh;
- Must be fluent in English;
- Must have an annual household income below £26,500;
- Must not be currently undertaking any regular medical treatment;
- Must not be pregnant.

We recruited participants using various advertisement channels, such as information leaflets delivered by post to home addresses in the more deprived neighborhoods in the vicinity of the University, online advertisements and promotional emails. All participants were given £50 compensation for participating in this study.

4.2 Procedure

Upon arriving at the BLUE lab, all participants were asked to measure their height and weight using the equipment provided (assistance was provided where necessary), and were also provided with individual tape measures in order to record their waist size. They were then directed to an individual computer in the laboratory. Participants were then asked to fill out an initial computer-based questionnaire which included questions related to demographics, socio-economic background, education, employment status, as well as various questions related to their prior knowledge regarding health, nutrition and their own health status. A snapshot of our sample's main characteristics is provided below in Table 3.

The first dietary measure we collected was a short-form food frequency questionnaire (FFQ), based on the US National Cancer Institute's Dietary Screener Questionnaire. The Dietary Screener lists a total of 23 food and drink items with specific descriptors (e.g. White fish in batter or breadcrumbs - like fish and chips), and respondents are asked to indicate the frequency with which they consumed each item over the last 30 days. The FFQ contains a total of eight (8) frequency options, ranging from 'Rarely or Never' to '5+ a day', with the exception of the seven meat and fish items (e.g. Beef, Lamb, Pork, Ham - steaks, roasts, joints, mince or chops) which had only six (6) options ranging from 'Rarely or Never' to 'At least everyday'. The National Cancer Institute's Dietary Screener Questionnaire has been subject to multiple evaluation studies, both in terms of the actual questions used as well as its overall performance and validity (e.g. Thompson et al., 2004; George et al., 2012). A copy of the actual FFQ administered to participants is provided in Appendix I. The questionnaire was self-administered by the participants, and on average took 7 minutes to complete.

Once all participants completed the FFQ, we then moved on to the next stage of the study – a 24-hour dietary recall. For the purposes of our study, we used a web-based self-administered tool called INTAKE24, whereby users are asked to input all the food and drink items consumed over the last 24 hours. The system has been devised specifically for the UK by Newcastle University in collaboration with Food Standards Scotland, and thus contains all the major food and drink brands typically consumed by UK households, including own-brand products by the leading supermarket chains. It also features visual indicators for portion sizes, and automatically prompts users to recall items which are typically overlooked in such self-reported tools, for example snacks, sauces, side-dishes, drinks and condiments. These prompts are repeated throughout the session to minimize the risk of under-reporting.[1] The use of web-based dietary recalls offers various advantages over traditional face-to-face interviews, including lower costs, the possibility of larger-scale studies across different cities, more individual privacy which may lead to improved accuracy of responses due to less pressure or embarrassment, and less interviewer-specific heterogeneities which may bias results. In fact, a number of studies (Arab et al., 2011; Baranowski et al., 2012) have shown that self-administered online dietary recalls yield data that are statistically-comparable in terms of accuracy to those derived from face-to-face recalls. A screenshot of the INTAKE24 user interface is provided in Appendix II.

The final measure of dietary choices analyzed in this study was our own food choice tool. At the start of this intervention, all participants were allocated a budget of £30 in order to spend on the food and drink items available from our tool. Participants were allowed to spend their budget on any of the items listed in the online supermarket, just as long as they did not exceed the £30 limit. We opted for a randomized incentive scheme, whereby at the end of each of our 20 sessions, one subject per session (maximum of 18 participants per session) was drawn at random and his/her food basket was delivered to his/her home address within one week at his/her preferred day and time slot by a leading UK supermarket. All subjects were informed of this arrangement beforehand, including the name of the supermarket, and were reminded prior to selecting their food and drink items[2]. In addition, participants were told to make their choices as though they were at their local supermarket for their weekly shop. While it is not obvious that participants will shop just for themselves these instructions can be made more specific if this is a concern to researchers using the tool. In our situation, if they were shopping for other members in the household, however, we would expect our shopping basket to be less likely to be correlated with body measurements. Once all participants had made their food and drink choices, lots were drawn to determine the winning participant and ensure that the process is as transparent and fair as possible.

[1]Prior to using the system, participants were asked to watch a step-by-step video tutorial showing how to utilize the INTAKE24 interface.

[2]Since participants had already utilized the food choice tool as part of another experimental session in June, this meant that they were fully aware of how the incentive scheme works. Additionally, this also ensured that all participants were familiar with the tool's user interface and were able to use it appropriately. During the June session participants were also given a mock tool containing everyday household items which they were encouraged to navigate and use beforehand in order to familiarize themselves with the actual food choice tool and its interface. To further ensure familiarity, a quick demonstration of the food choice tool was also presented to remind participants of the tool's features.

5 Results

5.1 Summary Statistics

We begin by looking at the nutrient data derived from each of our three measures. As described earlier, our proposed food choice tool contains nutritional information for each of the items displayed in the online supermarket interface, enabling us to derive the total nutrient content per basket (i.e. total calories per basket, total fats, etc.), as well as the nutrient content per £spent. Similarly, the INTAKE24 software has a database of over 1,560 food and drink items, each with a detailed breakdown of the nutrient content based on the portion size selected by the user.

The food frequency questionnaire (FFQ) is somewhat different, given that no information regarding portion sizes is recorded in the actual survey, thus complicating the conversion from frequency to nutrient intake. Nonetheless, for the purposes of our study we have developed a simple conversion protocol, inspired in part by existing methods widely used in the literature by Mulligan et al. (2014) and Thompson et al. (2005).

We first calculate the average nutrient content per 100g for each of the 23 food and drink categories listed in the FFQ, based on the most popular products sold at one of the UK's leading supermarkets for each category. The categories and food items associated with each category used in these calculations, together with their corresponding nutrient contents, are shown in Appendix III. The next step is to relate the responses from the FFQ to these nutrient values. As mentioned earlier, participants were asked to state the frequency with which they consumed items pertaining to each of the 23 categories, with 8 options ranging from 'Rarely or Never' to '5+ a day', with the exception of the seven meat and fish items which had only six options. We therefore convert these frequency responses to estimates of **daily** intake, by assigning a numerical value to each response based on average daily consumption frequency per week. For example, if a respondent indicated that s/he consumes a particular food/drink category 'Rarely or Never', then her/his response is assigned a value of 0; if her/his response was 'Once per week', then s/he is assigned a value of $1/7 = 0.14286$, reflecting the fact that on average this particular food category was only consumed once a week. We then multiply this value with the average nutrient value described above for each nutrient, to obtain an estimate of daily consumption of each nutrient.

So for example, if a subject recorded her cheese/yoghurt consumption over the last month as '1-2 times a day', then this would correspond to a numerical value of 1.5, which would then be multiplied with each average nutrient for cheese/yoghurt as listed in Appendix III to derive her nutritional intake for that particular category. For example, in this case her calorie intake for cheese/yoghurt would be $1.5x245.5 = 368.25$. Table 4 summarizes the average nutrient values of our participants from each of the three tools used in this study.

5.2 Comparison of Measures

We now move on to comparing the three measures utilized in this paper in order to see how well they correlate with one another. The rationale behind this analysis is that even though the 3 tools are distinct in their own right and yield different aggregate nutrient measures, they should still be capturing the same overall trend or composition, given that they are purportedly measuring the same indicators for the same sample of participants.

Table 5 reports the pairwise correlation matrices for each of the six nutrients measured from our three measurement tools: total calories, fat, saturated fat, carbohydrates, sugar and protein. Note that whereas both the 24-hour dietary recall and the food frequency questionnaire report estimates of intake for each nutrient per day (e.g. daily calorie intake for each subject), our food choice tool only estimates the total calorie content for the entire basket of food and drink items selected, and is hence not directly comparable to the other two measures. Nonetheless, it is still reasonable to expect that any nutrient values obtained via our food choice tool should a priori be correlated with those obtained from the other two self-reported measurement tools.

As seen below, the correlations across the three tools is somewhat mixed. We observe no correlations among any of the tools when it comes to calorie intake, fat and saturated fat, as seen from the first 3 panels. Nonetheless, the nutrient value for carbohydrate intake as captured by our proposed incentivized tool is correlated with the measure obtained from the the dietary recall, while the sugar intake measure is correlated with that obtained from both the 24-hour dietary recall and the FFQ. Similarly, the only correlations observed between the FFQ and the dietary recall are observed in terms of sugar and protein, which is interesting to note given that they are both self-reported measures of dietary intake. Therefore, although we do see some correlation across our proposed food choice tool and the other measures, the results also confirm the significant differences that exist between the three tools.

5.3 Relationship between Reported Calorie Intake and Biometric Indicators

We now compare the calorie measures from each tool to three common biometric indicators – weight (in kilograms), body-mass index (BMI) and waist size (in inches). The link between calorie intake and all three indicators has long been established in the literature (Newby et al., 2003; Guo et al., 2004; Romieu et al., 2004). Therefore, a positive and statistically-significant correlation between calorie intake as captured by our tools and each indicator is expected a priori. We focus exclusively on calorie intake rather than any of the other nutrient measures since, as pointed out by Livingstone and Black (2003) energy intake is the basis for one's diet, with all other nutrients "must be provided within the quantity of food needed to fulfill the energy requirement." Furthermore, the link between other nutrients like fat intake and each biometric indicator is not particularly robust or well-established (Newby et al., 2003), meaning that erroneous conclusions may be derived by focussing on these other nutrients.

Note that the intention here is not to determine the validity or otherwise of any of the three tools under consideration, particularly since we are only relying on a single calorie reading from each of the tools. In addition, the nutrition and epidemiology literature have used several methods to validate both the use of the FFQ as well as the 24-hour dietary recall, including cross-tool comparisons (Bingham et al, 1994) and the use of biomarkers like 24-hour urine collections (Bingham, 2002) and blood nutrient concentration (McKeown et al, 2001). Rather, the intention in this case is to see how closely our estimates correlate with key body measurements derived from our participants, which may in turn provide some evidence to support the use of our incentivized tool as a tractable measure of dietary intake in such studies, particularly when it is infeasible to take multiple dietary readings.

We therefore estimate the following equation:

$$B_i = \alpha + \beta_k C_{k,i} + \boldsymbol{X}'\gamma_j + \nu_{j,i} \tag{1}$$

where $B_{j,i}$ is one of the four biometric indicators mentioned above (height, weight, BMI) for subject i; $C_{k,i}$ is the amount of calories pertaining to subject i as captured by dietary assessment tool k; $\boldsymbol{X}$ is a vector of control variables like age, gender, socio-economic indicators and session-specific fixed effects[3], and $\nu_{j,i}$ is a random disturbance term.

The results are shown in Table 6, where each panel shows the results from estimating equation 1 for each of the dietary assessment methods used in this paper (calories have been normalized by 1,000). We can see that the only method whose measure of calorie intake correlates with the biometric indicators is our proposed food choice tool, as shown in Panel A. In fact, calorie intake from the food choice tool is positively and significantly-correlated with all four of the biometric indicators. The magnitudes of the coefficients of interest are somewhat low - for example a 10% increase in calorie intake is associated with a 1.5% increase in BMI. Nonetheless, the fact that our calorie intake measure is correlated with each biometric measure provides further evidence to support the use of our incentivized food choice tool as a measure of people's dietary intake. This is particularly true given that calorie intake from neither the 24-hour dietary recall (Panel B) nor from the food frequency questionnaire (FFQ) exhibit a statistically-significant correlation with any of the indicators used. Furthermore, although the slope coefficients for calories across the 3 tools are statistically-equivalent in magnitude when assessing weight, they are not statistically-equivalent for any of the other biometric measures.

There are two possible explanations for these null results: (i) a systematic misreporting of calorie intake by respondents when using both the FFQ and dietary recall, (ii) the presence of a substantial amount of noise in our data, which would raise standard errors and suppress

[3]A complete list of control variables used in this study is provided in Appendix IV

significance levels. The first explanation is related to recent evidence on the under-reporting of calorie intake in official statistics compiled by the UK government (Harper and Hallsworth, 2016). These data, which are collated using self-reported measures of dietary intake, have shown a persistent decline in calorie intake among the general population in recent years, despite the fact that average weight and BMI has been on the rise. This corresponds to the negative (albeit not statistically-significant) coefficients we observe on our calorie intake explanatory variables in Table 6 for both the recall and the FFQ. However, we cannot discount the second explanation either, since as pointed out earlier the nutrition literature typically advocates the administration of multiple 24-hour dietary recalls in order to reduce noise within the data. In our experiment, we only consider one reading from both tools as is often the case with limited time or budgets, meaning that any conclusions regarding the reliability or otherwise of these measures must be tempered somewhat by this consideration. Additionally, the closed nature of our food choice tool with its limited range of products may also have contributed towards lowering noise levels within the data relative to the other two measures.

5.3.1 Heterogeneity in Calorie Reporting

We now look at how the relationship between calorie intake as measured by our 3 tools and the various biometric measures varies within different subgroups. We examine different BMI groups as well as across both genders. The aim of this exercise is to see whether any subgroups are more prone to calorie under-reporting in our data. This analysis is motivated by the fact that various studies have shown that people who are obese or overweight are more likely to under-report their dietary intake (Lichtman et al., 1992).

Tables 7 and 8 below look at how the relationship between calorie intake and our biometric measures across the three tools varies by respondents' BMI grouping. For simplicity, we split our sample into 2 groups - those respondents whose BMI is 25 and above, i.e. the overweight and obese group (Table 7), and those with a BMI below 25, i.e. those with a normal weight relative to their height (Table 8). As seen from below, it seems as though the positive and significant relationship observed between calorie choices in our incentivized food choice tool and the biometric measures is mainly driven by those respondents who are either overweight or obese. This implies that the use of incentivized tools to measure calorific intake may be particularly appropriate for eliciting truthful responses from people who are either overweight or obese - typically the same cohort who as discussed earlier tend to under-report in typical dietary surveys. By contrast, we once again do not observe any statistically-significant results for the other two self-reported measures in Table 7, although when it comes to the FFQ we do find positive and significant coefficients in Table 8 when looking at people in the normal weight category. This indicates that self-reported measures like the FFQ may be appropriate for capturing the dietary patterns of people of normal weight, albeit insufficient when it comes to higher weight categories.

In tables 9 and 10 we perform a similar subgroup analysis, only this time analyzing differences according to gender. None of our estimates from any of our dietary measurement tools are statistically-significant for male participants (table 9). However, we do find positive and significant results for our female subgroup (table 10) when using our proposed food choice tool, across all biometric measures. Thus, it appears as though using incentivized tools for capturing dietary measures may be more effective for female participants rather than males, while self-reported measures are equally ineffective for both genders.

5.4 Sensitivity of Dietary Selection in Food Choice Tool

Having looked at our incentivized food choice tool as a predictor of people's biometric measurements and dietary intake, we now turn to assessing its functionality. More specifically, in this section we analyze the sensitivity of people's food choices to changes in the food/drink category first shown to participants upon logging into the system. In order to access the food choice tool, participants in the experiment were first asked to type in their username, after which the tool was loaded and they were immediately shown one of the six categories of food and drink items mentioned earlier, namely fruit and vegetables, meat and fish, bread and grains, confectionery and snacks, ready meals and drinks. The category displayed onscreen varied randomly across participants in order to avoid any systematic priming effects, and obviously participants were free to browse any of the other categories once the system loaded. Nonetheless, it is possible to assess whether initial exposure to any of these categories had any significant impact on both the type of food selected, as well as the nutrient content of their chosen food baskets. This is an important consideration, and is related to the substantial literature on mindless food choices and how people tend to opt for those food and drink items that are easily accessible, in various settings from supermarkets to restaurants and cafeterias (Wansink et al., 2009; Wisdom et al., 2010; Hanks et al., 2012). Thus, initial food category exposure may have some impact on participants' food choices in our tool, and must be taken into account and controlled for when conducting experiments or other studies using this tool.

Table 11 summarizes participants' initial exposure to each supermarket category in our food choice tool. As seen below, the initial category shown to participants upon login was fairly evenly-distributed across the six categories.

We can now formally assess whether initial exposure to any one of these 6 categories had any impact on participants' food and drink choices. We estimate the following equation:

$$Y_{ji} = \alpha + \sum_{k=1}^{5} \beta_{ki} Front_{ki} + \boldsymbol{X_i}'\gamma + \epsilon_i; \forall j \neq k \tag{2}$$

where Y_{ji} is our dependent variable, which in this case will be either total expenditure on each of the $j = \{1, 2, 3, 4, 5, 6\}$ supermarket categories by subject i, or the total number of items selected per category by i. Our explanatory variables of interest are represented by (6-1) five dummy variables $Front_{ki}$, whereby each dummy takes a value of 1 if subject i was first exposed to that particular food/drink category when using our food choice tool. To facilitate the interpretation of our results, we use the same baseline (omitted) category as the one used in our dependent variable. Thus for example, if we consider total expenditure on fruit and vegetables as our dependent variable, then the baseline or omitted category for our initial exposure dummies will be the fruit and vegetables category. The rationale behind this specification is that if initial exposure to a particular category led to increased expenditure on items pertaining to that same category, then all of the coefficients on the other category dummies should be negative and statistically-significant. $\boldsymbol{X_i}$ is the same vector of control variables used in table 6, with a full list of variables provided in Appendix IV.

Table 12 presents our findings. Panel A shows the results obtained when using total expenditure on each category as our dependent variable; Panel B uses the total number of items selected per category while Panel C utilizes the total nutrient content of each subject's chosen basket. As seen below, the results are somewhat mixed. We start with Panel A, column 1, where we observe negative and significant coefficients on both the confectionery and drinks categories, indicating that initial exposure to the fruit and veg category led to higher expenditure on fruit and veg relative to when the initial category was confectionery and drinks, to the tune of £3.12 and £2.62 respectively. The coefficients on the other categories are also negative, albeit not precisely estimated. In column 2 we also obtain a statistically-significant coefficient on the drinks category, although in this case it is *positive*, contrary to prior expectations. The rest of the results in the remaining columns are largely insignificant, indicating that on the whole there does not seem to be any systematic effect of initial category exposure on food expenditure.

Similarly mixed results are observed in Panel B, where we consider the total number of items selected in each category as our dependent variables. Once again we observe negative and significant coefficients in column 1 for confectionery, drinks and also ready meals, which provides some evidence that in this case initial exposure to fruit and veg did indeed increase subject's fruit and veg choices relative to the other categories. We also observe some systematic impact when it comes to bread and grains (column 3), where we have negative and significant coefficients on both confectionery and drinks, although the other category coefficients are not significant. Nonetheless, as before we also find a positive and significant coefficient on the drinks category in column 2 in relation to meat and fish, which would seemingly indicate that people exposed to the drinks category selected more meat items that participants whose initial category was meat and fish, contrary to expectations. Thus, although in this instance there is some evidence of systematic bias in the choices of participants based on which category they were initially exposed to (especially with regards to fruit and veg), overall this does not seem to be the case for most of our food and drink categories. Therefore, the pattern that emerges here is that although varying the initial category exposure in our food choice tool can have a significant impact on actual choices, there is limited evidence of this systematically nudging or boosting choices within the same category of exposure.

Finally, in Panel C we run similar regressions as in 2, only this time using the nutrient values (calories, fat, saturated fat, carbohydrates, sugar and protein) of each subject's food basket as our dependent variables. In this case, our baseline omitted category is always the drinks category. As expected, exposure to almost each of the categories led to a statistically-significant increase in both calorie and carbohydrate intake. This may be no surprise given that drinks are our reference category; however the results do seem to indicate that participants initially exposed to one of the food categories (except ready meals) on average chose items with more calories and more carbohydrates than those whose initial category was drinks. The actual differences in calorie and carbohydrate intake are not statistically-significant across the categories. The only other effect observed is that participants exposed to bread and grains initially chose food items with a higher sugar content, by about 25%, relative to those exposed to drinks. Therefore, the results in Panel C indicate that although there might not be any systematic influence of initial category exposure in terms of increased spending on the exposed category, there may still be some important impact in terms of the nutritional composition of one's choices. Thus, the results discussed in table 12 highlight the importance of taking this initial category exposure into account in any analysis that makes use of our proposed incentivized food choice tool.

6 Concluding Remarks

In this paper, we present and evaluate a new low-cost tool for eliciting information about food choices in an incentivized manner. People are allocated a fixed budget to spend on various food and drinks items from across six different categories, namely fruit and vegetables, meat and fish, bread and grains, confectionery and snacks, ready meals and drinks. The proposed food choice tool has several important benefits. Firstly, our tool can gather information regarding people's food choices in a relatively quick and inexpensive manner, without having to resort to multiple readings as with other tools used by nutritionists and epidemiologists. Secondly, the inherent flexibility of the tool means that it can be adjusted and tailored to suit a wide variety of research needs, and can be administered in various settings, even online. Thirdly, since our tool is designed to mimic an online supermarket, it captures a relatively wide variety of foods and drinks, encompassing a number of meals and snacks, thus enabling a more representative picture of people's dietary choices to be formulated. Finally, by incentivizing people's responses via the possibility of receiving their chosen food basket, this tool is able to avoid some of the pitfalls commonly associated with self-reported measures of dietary intake, particularly when it comes to misreporting (Burger and Owens, 2010).

To test out the functionality of our new tool, we conducted a lab experiment among 255 real-world participants at the University of Edinburgh's BLUE lab, whereby participants' dietary intake was recorded using three different tools, namely a food frequency questionnaire, a 24-hour dietary recall and our own food choice tool. Both the food frequency questionnaire and the dietary recall are heavily-used in the nutrition and epidemiology literature and have been validated, although both tools must be administered more than once in order to obtain more representative estimates of dietary intake. In addition, their reliability in terms of the representativeness of the measurements obtained has been called into question recently due to the fact that they both rely on self-reported dietary intake (Lichtman et al., 1992).

We first sought to compare the values for nutrient profile across each of the three tools to see how well they match up to one another. The results were somewhat mixed, although no statistically-significant correlation was observed across the tools when considering calories, fat and saturated fat. We then proceeded to compare the total calorie intake recorded for each subject by the three tools to a number of individual biometric measures which are known to be positively-correlated with calorie intake, namely weight, body mass index (BMI) and waist size. The results showed that only the calorie intake measure from our incentivized food choice tool was positively and significantly related to each of the four biometric measures. By contrast, the calorie measures obtained from both the food frequency questionnaire and the 24 hour dietary recall were not significantly related to *any* of the biometric measures under consideration. Analysis of different subgroups within our sample showed that the positive and significant correlation observed for our incentivized tool was mainly driven by overweight or obese participants, which must be seen in light of recent evidence on under-estimation of calorie intake among this cohort when using self-reported measurement tools like a food frequency questionnaire or a 24 hour dietary recall (Harper and Hallsworth, 2016).

Finally, we examined whether our food choice tool was sensitive to particular design choices, specifically by assessing whether variation in the initial category of food that participants were exposed to upon accessing the tool had any impact on their actual choices. The results were somewhat scattered, with limited evidence that initial exposure had any impact on encouraging greater purchases from that same category, although we did find some statistically-significant impacts across categories. Thus, these findings showed the importance of adequately controlling for initial category exposure when conducting any work based on this tool.

The findings in this paper provide further evidence that incentive-based tools for information elicitation can provide significant benefits in terms of capturing people's underlying preferences and behaviors. Amidst growing concern regarding self-reported data in surveys, this study highlights the possibility of integrating novel techniques that incentivize truthful responses into standard surveys across a wide range of applications, while keeping issues related to cost and practicality in check. This paper also lends further credence to the concerns raised in Bertrand and Mullainathan (2001) and Harper and Hallsworth (2016) regarding the systematic biases in self-reported survey responses, and thus the need to control for such errors when conducting any empirical investigation.

References

Adamowicz, Wiktor, Peter Boxall, Michael Williams, and Jordan Louviere, "Stated preference approaches for measuring passive use values: choice experiments and contingent valuation," *American journal of agricultural economics*, 1998, *80* (1), 64–75.

Alfnes, Frode, Atle G Guttormsen, Gro Steine, and Kari Kolstad, "Consumers' willingness to pay for the color of salmon: a choice experiment with real economic incentives," *American Journal of Agricultural Economics*, 2006, *88* (4), 1050–1061.

Arab, Lenore, Chi-Hong Tseng, Alfonso Ang, and Patricia Jardack, "Validity of a multipass, web-based, 24-hour self-administered recall for assessment of total energy intake in blacks and whites," *American journal of epidemiology*, 2011, p. kwr224.

Baranowski, Tom, Noemi Islam, Janice Baranowski, Shelby Martin, Alicia Beltran, Hafza Dadabhoy, Su heyla Adame, Kathleen B Watson, Debbe Thompson, Karen W Cullen et al., "Comparison of a web-based versus traditional diet recall among children," *Journal of the Academy of Nutrition and Dietetics*, 2012, *112* (4), 527–532.

Baumeister, Roy F, "Yielding to temptation: Self-control failure, impulsive purchasing, and consumer behavior," *Journal of consumer Research*, 2002, *28* (4), 670–676.

Belot, Michèle, Jonathan James, and Jonathan Spiteri, "Health Information, Prioritization and Dietary Choices: Evidence from a Laboratory Experiment," *Unpublished mimeo*, 2016.

Berg, Joyce E, John W Dickhaut, and Thomas A Rietz, "Preference reversals: The impact of truth-revealing monetary incentives," *Games and Economic Behavior*, 2010, *68* (2), 443–468.

Bertrand, Marianne and Sendhil Mullainathan, "Do people mean what they say? Implications for subjective survey data," *The American Economic Review*, 2001, *91* (2), 67–72.

Block, Gladys et al., "A review of validations of dietary assessment methods," *American journal of epidemiology*, 1982, *115* (4), 492–505.

Bollinger, Bryan, Phillip Leslie, and Alan Sorensen, "Calorie posting in chain restaurants," *American Economic Journal: Economic Policy*, 2011, *3* (1), 91–128.

Burger, Ronelle and Trudy Owens, "Promoting transparency in the NGO sector: Examining the availability and reliability of self-reported data," *World development*, 2010, *38* (9), 1263–1277.

Cade, JE, VJ Burley, DL Warm, RL Thompson, and BM Margetts, "Food-frequency questionnaires: a review of their design, validation and utilisation," *Nutrition research reviews*, 2004, *17* (01), 5–22.

Carlsson, Fredrik, Peter Frykblom, and Carl Johan Lagerkvist, "Consumer benefits of labels and bans on GM foodschoice experiments with Swedish consumers," *American Journal of Agricultural Economics*, 2007, *89* (1), 152–161.

Chang, Jae Bong, Jayson L Lusk, and F Bailey Norwood, "How closely do hypothetical surveys and laboratory experiments predict field behavior?," *American Journal of Agricultural Economics*, 2009, *91* (2), 518–534.

Cowburn, Gill and Lynn Stockley, "Consumer understanding and use of nutrition labelling: a systematic review," *Public health nutrition*, 2005, *8* (01), 21–28.

Cubitt, Robin P, Chris Starmer, and Robert Sugden, "On the validity of the random lottery incentive system," *Experimental Economics*, 1998, *1* (2), 115–131.

Dalstra, Jetty AA, Anton E Kunst, Carme Borrell, Elizabeth Breeze, Emmanuelle Cambois, Giuseppe Costa, José JM Geurts, Eero Lahelma, Herman Van Oyen, Niels K Rasmussen et al., "Socioeconomic differences in the prevalence of common chronic diseases: an overview of eight European countries," *International journal of epidemiology*, 2005, *34* (2), 316–326.

Diener, Alan, Bernie O'Brien, and Amiram Gafni, "Health care contingent valuation studies: a review and classification of the literature," *Health economics*, 1998, *7* (4), 313–326.

Elbel, Brian, Rogan Kersh, Victoria L Brescoll, and L Beth Dixon, "Calorie labeling and food choices: a first look at the effects on low-income people in New York City," *Health affairs*, 2009, *28* (6), w1110–w1121.

et al. Beaton G.H., J. Milner P. Corey V. McGuire, "Sources of variance in 24-hour dietary recall data: Implications for nutrition study design and interpretation," *American Journal of Clinical Nutrition*, 1979, *32*, 2546–59.

George, Stephanie M, Frances E Thompson, Douglas Midthune, Amy F Subar, David Berrigan, Arthur Schatzkin, and Nancy Potischman, "Strength of the relationships between three self-reported dietary intake instruments and serum carotenoids: the Observing Energy and Protein Nutrition (OPEN) Study," *Public health nutrition*, 2012, *15* (06), 1000–1007.

Gonyea, Robert M, "Self-reported data in institutional research: Review and recommendations," *New directions for institutional research*, 2005, *127*, 73.

Graham, Dan J and Robert W Jeffery, "Location, location, location: Eye-tracking evidence that consumers preferentially view prominently positioned nutrition information," *Journal of the American Dietetic Association*, 2011, *111* (11), 1704–1711.

Griffith, Rachel and Martin O'Connell, "The use of scanner data for research into nutrition," *Fiscal Studies*, 2009, *30* (3-4), 339–365.

_ and _ , "Public policy towards food consumption," *Fiscal Studies*, 2010, *31* (4), 481–507.

_ , Martin OConnell, and Kate Smith, "Relative prices, consumer preferences, and the demand for food," *Oxford Review of Economic Policy*, 2015, *31* (1), 116–130.

Guo, X, BA Warden, S Paeratakul, and GA Bray, "Healthy eating index and obesity," *European journal of clinical nutrition*, 2004, *58* (12), 1580–1586.

Hanks, Andrew S, David R Just, Laura E Smith, and Brian Wansink, "Healthy convenience: nudging students toward healthier choices in the lunchroom," *Journal of Public Health*, 2012, p. fds003.

Harper, Hugo and Michael Hallsworth, "Counting calories: How under-reporting can explain the apparent fall in calorie intake," *Behavioural Insights Team*, 2016.

Johnson, Rachel K, "Dietary intake - how do we measure what people are really eating?," *Obesity research*, 2002, *10* (11), 63S–68S.

Jr, John G Lynch and Gal Zauberman, "When do you want it? Time, decisions, and public policy," *Journal of Public Policy & Marketing*, 2006, *25* (1), 67–78.

Kollat, David T and Ronald P Willett, "Customer impulse purchasing behavior," *Journal of marketing research*, 1967, pp. 21–31.

Kozup, John C, Elizabeth H Creyer, and Scot Burton, "Making healthful food choices: the influence of health claims and nutrition information on consumers evaluations of packaged food products and restaurant menu items," *Journal of Marketing*, 2003, *67* (2), 19–34.

Kristal, Alan R, Ann L Shattuck, and Allen E Williams, "Food frequency questionnaires for diet intervention research," in "Proceedings of the 17th National Nutrient Databank Conference" International Life Sciences Institute, Baltimore, Md. Washington, DC 1992, pp. 110–125.

Lichtman, Steven W, Krystyna Pisarska, Ellen Raynes Berman, Michele Pestone, Hillary Dowling, Esther Offenbacher, Hope Weisel, Stanley Heshka, Dwight E Matthews, and Steven B Heymsfield, "Discrepancy between self-reported and actual caloric intake and exercise in obese subjects," *New England Journal of Medicine*, 1992, *327* (27), 1893–1898.

List, John A and Craig A Gallet, "What experimental protocol influence disparities between actual and hypothetical stated values?," *Environmental and Resource Economics*, 2001, *20* (3), 241–254.

Livingstone, M Barbara E and Alison E Black, "Markers of the validity of reported energy intake," *The Journal of nutrition*, 2003, *133* (3), 895S–920S.

Loomis, John, Paul Bell, Helen Cooney, Cheryl Asmus et al., "A comparison of actual and hypothetical willingness to pay of parents and non-parents for protecting infant health: the case of nitrates in drinking water," *Journal of Agricultural and Applied Economics*, 2009, *41* (3), 697–712.

Lusk, Jayson L and Ted C Schroeder, "Are choice experiments incentive compatible? A test with quality differentiated beef steaks," *American Journal of Agricultural Economics*, 2004, *86* (2), 467–482.

Macdiarmid, Jennie and John Blundell, "Assessing dietary intake: who, what and why of under-reporting," *Nutrition research reviews*, 1998, *11* (02), 231–253.

McFerran, Brent, Darren W Dahl, Gavan J Fitzsimons, and Andrea C Morales, "Ill have what shes having: Effects of social influence and body type on the food choices of others," *Journal of Consumer Research*, 2010, *36* (6), 915–929.

Mulligan, Angela A, Robert N Luben, Amit Bhaniani, David J Parry-Smith, Laura O'Connor, Anthony P Khawaja, Nita G Forouhi, Kay-Tee Khaw, Adam Dickinson, Nick Wareham et al., "A new tool for converting food frequency questionnaire data into nutrient and food group values: FETA research methods and availability," *BMJ open*, 2014, *4* (3), e004503.

Newby, P Kristen, Denis Muller, Judith Hallfrisch, Ning Qiao, Reubin Andres, and Katherine L Tucker, "Dietary patterns and changes in body mass index and waist circumference in adults," *The American journal of clinical nutrition*, 2003, *77* (6), 1417–1425.

Podsakoff, Philip M and Dennis W Organ, "Self-reports in organizational research: Problems and prospects," *Journal of management*, 1986, *12* (4), 531–544.

Raghavarao, Damaraju and Walter T Federer, "Block total response as an alternative to the randomized response method in surveys," *Journal of the Royal Statistical Society. Series B (Methodological)*, 1979, pp. 40–45.

Resnicow, Kenneth, Erica Odom, Terry Wang, William N Dudley, Diane Mitchell, Roger Vaughan, Alice Jackson, and Thomas Baranowski, "Validation of three food frequency questionnaires and 24-hour recalls with serum carotenoid levels in a sample of African-American adults," *American Journal of Epidemiology*, 2000, *152* (11), 1072–1080.

Romieu, Isabelle, David M Mannino, Stephen C Redd, and Michael A McGeehin, "Dietary intake, physical activity, body mass index, and childhood asthma in the Third National Health And Nutrition Survey (NHANES III)," *Pediatric pulmonology*, 2004, *38* (1), 31–42.

Shim, Jee-Seon, Kyungwon Oh, and Hyeon Chang Kim, "Dietary assessment methods in epidemiologic studies," *Epidemiology and health*, 2014, *36*, e2014009.

Starmer, Chris and Robert Sugden, "Does the random-lottery incentive system elicit true preferences? An experimental investigation," *The American Economic Review*, 1991, *81* (4), 971–978.

Stern, Hawkins, "The significance of impulse buying today," *The Journal of Marketing*, 1962, pp. 59–62.

Thomas, Manoj, Kalpesh Kaushik Desai, and Satheeshkumar Seenivasan, "How credit card payments increase unhealthy food purchases: visceral regulation of vices," *Journal of consumer research*, 2011, *38* (1), 126–139.

Thompson, Frances E, Douglas Midthune, Amy F Subar, Lisa L Kahle, Arthur Schatzkin, and Victor Kipnis, "Performance of a short tool to assess dietary intakes of fruits and vegetables, percentage energy from fat and fibre," *Public health nutrition*, 2004, *7* (08), 1097–1106.

_ , _ , _ , Timothy McNeel, David Berrigan, and Victor Kipnis, "Dietary intake estimates in the National Health Interview Survey, 2000: methodology, results, and interpretation," *Journal of the American Dietetic Association*, 2005, *105* (3), 352–363.

Wansink, Brian, David Just, and Collin R Payne, "Mindless eating and healthy heuristics for the irrational," *American Economic Review*, 2009, *99*, 165.

Warner, Stanley L, "Randomized response: A survey technique for eliminating evasive answer bias," *Journal of the American Statistical Association*, 1965, *60* (309), 63–69.

Wisdom, Jessica, Julie S Downs, and George Loewenstein, "Promoting healthy choices: Information versus convenience," *American Economic Journal: Applied Economics*, 2010, *2* (2), 164–178.

Tables & Figures

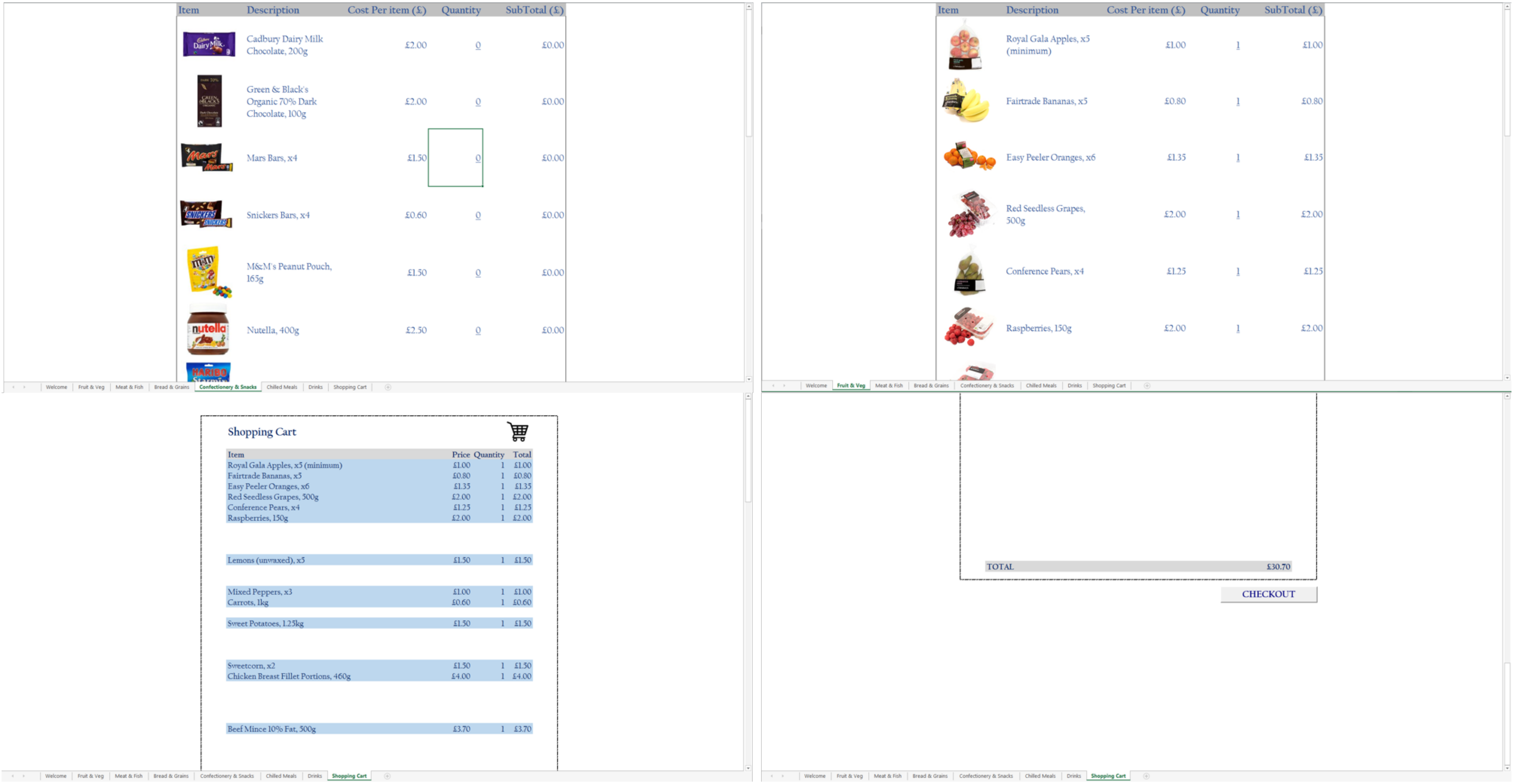


Figure 1: Screenshots of the Food Choice Tool

Table 1: List of Food and Drink Items in the Food Choice Tool

Fruit and Veg	**Meat and Fish**	**Bread and Grains**
Royal Gala Apples, x5	Chicken Breast Fillets, 460g	Sliced White Bread, 800g
Fairtrade Bananas, x5	Chicken Kiev, Garlic, x2	Sliced 50/50 Bread, 800g
Oranges, x6	Chicken Goujons, 245g	Sliced Wholemeal Bread, 800g
Red Grapes, 500g	Chicken Pie, 550g	White Baguettes, x2
Conference Pears, x4	Beef Rump Steak, 250g	Brown Baguettes, x2
Raspberries, 150g	Beef Mince, 500g	White Rolls, x8
Strawberries, 400g	Steak Burgers, 340g	Wholemeal Rolls, x8
Peaches, x4	Steak and Ale Pie, 550g	Crumpets, 400g
Kiwi Fruit, x4	Pork Chops, 450g	Plain Naan Bread, 260g
Lemons, x5	Pork Sausages, 400g	Brown Soda Bread, 400g
Cherry Tomatoes, 650g	Mini Pork Pies, 300g	Tortilla Wraps, x8
White Mushrooms, 300g	Smoked Bacon, 300g	Basmati Rice, 1kg
Maris Piper Potatoes, 2.5kg	Lamb Chops, 275g	Brown Basmati Rice, 1kg
Sweet Potatoes, 1.25kg	Salmon fillets, 240g	Penne Pasta, 1kg
Mixed Peppers, x3	Cod fillets, 250g	Wholewheat Penne, 1kg
Carrots, 1kg	Sea Bass Fillets, 180g	Spaghetti, 500g
Onions, 1kg	King Prawns, 150g	Wholewheat Spaghetti, 500g
Fine Beans, 200g	Breaded Cod, 350g	Cous Cous, 1kg
Broccoli, 335g	Smoked Haddock with Cheese, 400g	Quinoa, 300g
Sweetcorn, x2	Salmon en Croute, 380g	Egg Noodles, 375g
	Cod Fish Fingers, 480g	
	Mackerel in Garlic Butter, 340g	
Confectionery	**Ready Meals**	**Drinks**
Dairy Milk Chocolate, 200g	Cheese & Tomato Pizza, 10”	Blackcurrant Squash, 850ml
70% Dark Chocolate, 100g	Pepperoni Pizza, 10”	Orange & Passion Fruit Drink, 4x275ml
Mars Bars, x4	Beef Lasagne, 430g	Coconut Water, 1L
Snickers, x4	Macaroni Cheese, 430g	Sports Drink, 1L
M&M’s Peanut, 165g	Chicken & Bacon Pasta Bake, 430g	Energy Drink, 1L
Nutella, 400g	Cottage Pie, 450g	Ginger Beer, 1.5L
Starmix Candy, 215g	Beef Stew, 450g	Tonic Water, 1L
Jelly Babies, 190g	Chicken Tikka & Rice, 500g	Coke, 1.75L
Marshmallows, 200g	Beef Burrito, 400g	Irn Bru, 2L
Chocolate Chip Brioche, x8	Chicken Chow Mein, 450g	Fanta, 2L
Chocolate Digestives, 300g	Beef Satay, 380g	Orange Juice, 1L
Chocolate HobNobs, 262g	Chicken Ramen, 380g	Mango & Passion Fruit Smoothie, 750ml
Shortbread Fingers, 400g	Pigs in Blankets, 260g	Still Water, 6x500ml
Custard Creams, 400g	Vegetarian Cannelloni, 430g	Chocolate Milkshake, 1L
Chocolate Cookies, 175g	Vegetable Spring Rolls, 60g	Soya Milk, 1L
Pringles Original, 190g	Vegetable Biryani, 500g	
Salt & Vinegar Chips, 150g	Tomato & Mozzarella Bake, 430g	
Cheese & Onion Crisps, 6x25g	Lentil Cottage Pie, 400g	
Corn Chips, 200g	Mushroom Risotto, 430g	
Croissants, x8	Tomato Soup, 600g	

Note: In this table we list all of the 120 food and drink items included in our proposed Food Choice tool, under each respective category.

Table 2: Average Nutrient Content per Category (per 100g)

Calories	**Fat**	**Sat Fat**	**Carbs**	**Sugar**	**Protein**	
Fruit and Veg	47.4	0.5	0.1	9.7	7.2	1.4
Meat and Fish	233.2	13.9	4.9	7.5	0.8	19.4
Bread and Grains	212.1	1.9	0.4	40.6	2.4	7.0
Confectionery	471.9	22.5	9.1	59.4	33.1	6.4
Ready Meals	157.7	6.9	2.6	15.3	2.6	7.1
Drinks	40.5	0.2	0.1	9.9	9.2	0.6

Note: This table summarizes the average nutrient content, per 100g, of each of the six food and drink categories used as part of our proposed food choice tool. We consider six key nutrients, namely calories (in kcal), fat, saturated fat, carbohydrates, sugar and protein.

Table 3: Baseline Characteristics of Sample

Variable	**Mean**	**Std. Dev.**
% Males	37.6%	48.5
% White	87.8%	32.7
Married	67.5%	46.9
Age	36.9	11.426
Employed	58.0%	49.4
Unemployed	8.6%	28.1
Income above £25,000	7.1%	25.7
Income £20,000-25,000	30.2%	46
Income £15,000-20,000	21.6%	41.2
Income £10,000-15,000	21.2%	40.9
Income £5,000-10,000	12.5%	33.2
Weight	72.9	16.977
BMI	25.4	5.357
Waist	33.3	6.734
Blood Sugar Normal	89.8%	30.3
Family History Heart Disease	20.8%	40.7
Regular Diet	77.6%	41.7
Vegetarian	15.3%	36.1
Smoker	16.5%	37.2
N	255	

Note: This table provides a summary of the key characteristics of the sample used as part of this study. In total, our sample consists of 255 participants, who were recruited from the surrounding precincts of the University of Edinburgh's main campus in the city of Edinburgh. To be eligible to participate in this study, participants were required to have a good understanding of English, an annual household income below £26,500, no pre-existing medical conditions and not be pregnant.

Table 4: Nutrient Measures from each Dietary Assessment Tool

Variable	Mean	Std. Dev.	Min.	Max.
1. Food Choice Tool				
Calories per Basket	10137.845	2899.308	1137	18678.26
Fat per Basket	252.122	102.637	9.75	603.1
Saturated Fat per Basket	86.858	43.95	1.95	242.48
Carbohydrates per Basket	1440.242	592.87	6.61	3182.7
Sugar per Basket	594.055	258.39	6.61	1636.27
Protein per Basket	477.628	153.035	115.882	1026.76
2. 24-Hour Dietary Recall				
Calories per day	2032.167	1196.181	368.92	12900.21
Fat per day	83.376	73.092	0.54	912.930
Saturated Fat per day	31.147	33.401	0.34	458.55
Carbohydrates per day	240.152	132.22	18.39	992.84
Sugar per day	102.4	69.035	4.76	510.33
Protein per day	74.47	41.159	2.61	351.31
3. Food Frequency Questionnaire				
Calories per day	1320.178	662.412	209.912	5981.814
Fat per day	51.252	33.264	4.903	320.869
Saturated Fat per day	21.324	15.999	1.555	192.185
Carbohydrates per day	151.273	77.428	17.803	582.962
Sugar per day	62.958	35.387	10.812	347.406
Protein per day	55.855	25.583	9.352	182.188
N		255		

Note: This table lists the average measurements for each nutrient, obtained from the three measures of dietary intake employed in this study, namely our own proposed food choice tool, a 24-hour dietary recall and a food frequency questionnaire (FFQ). The six nutrients measured are calories (in kcal), fat, saturated fat, carbohydrates, sugar and protein (all in grams). Both the 24-hour dietary recall and the FFQ report average nutrient intake per day, whereas our food choice tool reports the average nutrient content of each participant's chosen food and drink basket.

Table 5: Correlation Matrices for Dietary Intake Measures

(1) Calories	Food Choice Tool	Recall	FFQ
Food Choice Tool	1		
Recall	0.06	1	
FFQ	0.05	0.05	1
(2) Fat	Food Choice Tool	Recall	FFQ
Food Choice Tool	1		
Recall	0.01	1	
FFQ	0.09	0.07	1
(3) Saturated Fat	Food Choice Tool	Recall	FFQ
Food Choice Tool	1		
Recall	0.06	1	
FFQ	0.10	0.07	1
(4) Carbs	Food Choice Tool	Recall	FFQ
Food Choice Tool	1		
Recall	0.13**	1	
FFQ	0.11	0.07	1
(5) Sugar	Food Choice Tool	Recall	FFQ
Food Choice Tool	1		
Recall	0.16**	1	
FFQ	0.21**	0.16**	1
(6) Protein	Food Choice Tool	Recall	FFQ
Food Choice Tool	1		
Recall	0.11	1	
FFQ	0.08	0.19**	1

Note: Asterisks (**) denote variables significant at 5% level. This table reports the pairwise correlations for the three measures of dietary intake used in this study, namely our proposed food choice tool, a 24-hour dietary recall and a food frequency questionnaire (FFQ), across the six nutrient measures under consideration, namely calories, fat, saturated fat, carbohydrates, sugar and protein. The idea is to assess how the measurements for each nutrient derived from each tool correlate with one another.

Table 6: Validity of Dietary Assessment Tools

	(1) Weight	(2) BMI	(3) Waist
Panel A: Food Choice Tool			
Supermarket Calories	0.733*	0.369**	0.564***
	(0.386)	(0.150)	(0.209)
Constant	35.12***	17.00***	25.39***
	(12.68)	(4.006)	(3.906)
Panel B: 24-Hr Dietary Recall			
Recall Calories	-0.490	-0.425	-0.257
	(0.917)	(0.274)	(0.267)
Constant	43.80***	21.74***	31.81***
	(13.04)	(3.818)	(4.495)
Panel C: Food Frequency Questionnaire			
FFQ Calories	0.692	-0.215	-0.17
	(1.469)	(0.477)	(0.49)
Constant	41.91**	21.11***	31.474***
	(12.52)	(3.7)	(4.48)
Controls	Y	Y	Y
Observations	255	255	255

Note: Robust standard errors in parentheses. Asterisks (***), (**) and (*) denote variables significant at 1%, 5% and 10% levels respectively. This table reports the results from our linear regression estimates of equation 1. In each panel, we regress the subjects' biometric measures (weight, body-mass index and waist size) on the calorie intake values obtained from each of the dietary intake measurement tools, namely the food choice tool, the 24 hour dietary recall and the food frequency questionnaire (FFQ), along with a number of control variables (listed in Appendix IV). Note that for aesthetic reasons, in each panel calories have been multiplied by 1,000, and thus any coefficient estimates must be interpreted appropriately.

Table 7: Subgroup Analysis - BMI 25 and Over

	(1) Weight	(2) BMI	(3) Waist
Panel A: Food Choice Tool			
Supermarket Calories	0.858	0.570**	0.369*
	(0.628)	(0.258)	(0.210)
Constant	38.15	21.62***	32.24***
	(25.17)	(5.727)	(5.396)
Panel B: 24-Hr Dietary Recall			
Recall Calories	1.20	0.183	0.345
	(1.40)	(0.444)	(0.446)
Constant	46.74*	28.32***	36.21***
	(24.46)	(4.902)	(4.821)
Panel C: Food Frequency Questionnaire			
FFQ Calories	1.04	-0.0806	0.139
	(2.90)	(0.795)	(0.966)
Constant	48.21**	28.65***	36.71***
	(24.07)	(4.711)	(4.747)
Controls	Y	Y	Y
Observations	114	114	114

Note: Robust standard errors in parentheses. Asterisks (***), (**) and (*) denote variables significant at 1%, 5% and 10% levels respectively. This table reports the results from our linear regression estimates of equation 1, only this time focusing solely on those subjects whose body-mass-index (BMI) is 25 or over. The idea behind this subgroup analysis is to assess whether the results presented in 6 differ among those subjects who are classified as being either overweight or obese (relative to their height). In each panel, we once again regress the subjects' biometric measures (weight, body-mass index and waist size) on the calorie intake values obtained from each of the dietary intake measurement tools, namely the food choice tool, the 24 hour dietary recall and the food frequency questionnaire (FFQ), along with a number of control variables (listed in Appendix IV). Note that for aesthetic reasons, in each panel calories have been multiplied by 1,000, and thus any coefficient estimates must be interpreted appropriately. Robust standard errors are used.

Table 8: Subgroup Analysis - BMI Under 25

	(1) Weight	(2) BMI	(3) Waist
Panel A: Food Choice Tool			
Supermarket Calories	0.0130	-0.0129	0.442
	(0.278)	(0.0645)	(0.295)
Constant	60.38***	23.59***	26.63***
	(8.651)	(1.804)	(4.776)
Panel B: 24-Hr Dietary Recall			
Recall Calories	-0.382	-0.367**	-0.262
	(0.951)	(0.169)	(0.236)
Constant	61.38***	24.30***	31.69***
	(9.786)	(1.667)	(5.332)
Panel C: Food Frequency Questionnaire			
FFQ Calories	2.27**	0.242	-0.0233
	(1.00)	(0.272)	(0.553)
Constant	56.87***	23.07***	31.13***
	(9.181)	(1.699)	(5.742)
Controls	Y	Y	Y
Observations	141	141	141

Note: Robust standard errors in parentheses Asterisks (***), (**) and (*) denote variables significant at 1%, 5% and 10% levels respectively. This table reports the results from our linear regression estimates of equation 1, only this time focusing solely on those subjects whose body-mass-index (BMI) is below 25. The idea behind this subgroup analysis is to assess whether the results presented in 6 differ among those subjects who are classified as being of normal weight (relative to their height). In each panel, we once again regress the subjects' biometric measures (weight, body-mass index and waist size) on the calorie intake values obtained from each of the dietary intake measurement tools, namely the food choice tool, the 24 hour dietary recall and the food frequency questionnaire (FFQ), along with a number of control variables (listed in Appendix IV). Note that for aesthetic reasons, in each panel calories have been multiplied by 1,000, and thus any coefficient estimates must be interpreted appropriately.

Table 9: Subgroup Analysis - Male Participants

	(1) Weight	(2) BMI	(3) Waist
Panel A: Food Choice Tool			
Supermarket Calories	-0.0327	-0.0950	0.486
	(0.461)	(0.146)	(0.340)
Constant	59.59***	19.87***	37.73***
	(17.25)	(5.306)	(7.412)
Panel B: 24-Hr Dietary Recall			
Recall Calories	-0.110	-0.431	0.0549
	(1.51)	(0.438)	(0.381)
Constant	59.45***	19.86***	45.28***
	(16.94)	(5.512)	(9.936)
Panel C: Food Frequency Questionnaire			
FFQ Calories	-0.983	-0.843	0.519
	(2.72)	(0.778)	(1.14)
Constant	60.31***	19.43***	44.81***
	(14.87)	(4.959)	(10.17)
Controls	Y	Y	Y
Observations	96	96	96

Note: Robust standard errors in parentheses. Asterisks (***), (**) and (*) denote variables significant at 1%, 5% and 10% levels respectively. This table reports the results from our linear regression estimates of equation 1, only this time focusing solely on male subjects. The idea behind this subgroup analysis is to assess whether the results presented in 6 differ among men. In each panel, we once again regress the subjects' biometric measures (weight, body-mass index and waist size) on the calorie intake values obtained from each of the dietary intake measurement tools, namely the food choice tool, the 24 hour dietary recall and the food frequency questionnaire (FFQ), along with a number of control variables (listed in Appendix IV). Note that for aesthetic reasons, in each panel calories have been multiplied by 1,000, and thus any coefficient estimates must be interpreted appropriately.

Table 10: Subgroup Analysis - Female Participants

	(1) Weight	(2) BMI	(3) Waist
Panel A: Food Choice Tool			
Supermarket Calories	1.11*	0.572***	0.450**
	(0.567)	(0.215)	(0.185)
Constant	33.88**	17.29***	25.15***
	(15.09)	(4.938)	(4.613)
Panel B: 24-Hr Dietary Recall			
Recall Calories	-1.00	-0.414	-0.455
	(1.32)	(0.406)	(0.332)
Constant	45.85***	23.28***	30.11***
	(15.36)	(4.864)	(4.528)
Panel C: Food Frequency Questionnaire			
FFQ Calories	1.06	-0.000769	-0.137
	(1.96)	(0.629)	(0.615)
Constant	42.78***	22.50***	29.40***
	(14.78)	(4.677)	(4.440)
Controls	Y	Y	Y
Observations	159	159	159

Note: Robust standard errors in parentheses. Asterisks (***), (**) and (*) denote variables significant at 1%, 5% and 10% levels respectively. This table reports the results from our linear regression estimates of equation 1, only this time focusing solely on female subjects. The idea behind this subgroup analysis is to assess whether the results presented in 6 differ among females. In each panel, we once again regress the subjects' biometric measures (weight, body-mass index and waist size) on the calorie intake values obtained from each of the dietary intake measurement tools, namely the food choice tool, the 24 hour dietary recall and the food frequency questionnaire (FFQ), along with a number of control variables (listed in Appendix IV). Note that for aesthetic reasons, in each panel calories have been multiplied by 1,000, and thus any coefficient estimates must be interpreted appropriately.

Table 11: Initial Category Exposure in Food Choice Tool

Variable	**Mean**	**Std. Dev.**
Fruit and Veg	12.9%	33.6
Meat and Fish	17.3%	37.9
Bread and Grains	18%	38.5
Confectionery	17.6%	38.2
Ready Meals	16.1%	36.8
Drinks	18%	38.5
N	255	

Note: This table shows the proportion of subjects who, upon accessing the food choice tool, were initially exposed to each of the six food and drink categories available, namely fruit and vegetables, meat and fish, bread and grains, confectionery and snacks, ready meals and drinks.

Table 12: Sensitivity of Food Choices to Initial Category Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total Expenditure per Category	**Fruit**	**Meat**	**Bread**	**Confec**	**Ready**	**Drinks**
Front Fruit		0.00308	0.651	-0.811*	-1.595*	0.00129
		(1.703)	(0.609)	(0.488)	(0.931)	(0.648)
Front Meat	-0.821		-0.327	-0.0967	-0.796	0.115
	(1.122)		(0.488)	(0.430)	(1.015)	(0.572)
Front Bread	-0.895	-1.069		0.591	-1.173	0.539
	(1.194)	(1.390)		(0.509)	(1.087)	(0.594)
Front Conf	-3.123**	1.768	0.0561		-0.720	-0.326
	(1.216)	(1.468)	(0.555)		(1.131)	(0.563)
Front Ready	-1.739	0.571	-0.831*	-0.410		0.592
	(1.149)	(1.482)	(0.446)	(0.460)		(0.715)
Front Drinks	-2.362**	2.804**	-0.668	-0.0418	-1.579	
	(1.116)	(1.383)	(0.454)	(0.469)	(1.115)	
Constant	14.24***	13.84***	1.605	1.270	2.003	0.294
	(2.967)	(3.834)	(1.407)	(1.257)	(1.845)	(1.600)
Panel B: Items Chosen per Category	**Fruit**	**Meat**	**Bread**	**Confec**	**Ready**	**Drinks**
Front Fruit		0.0369	0.356	-0.604**	-0.632*	-0.186
		(0.511)	(0.452)	(0.290)	(0.382)	(0.261)
Front Meat	-0.958		-0.399	-0.157	-0.353	0.0512
	(0.795)		(0.360)	(0.262)	(0.405)	(0.233)
Front Bread	-0.882	-0.303		0.339	-0.458	0.291
	(0.918)	(0.410)		(0.307)	(0.446)	(0.232)
Front Conf	-2.337**	0.547	0.0325		-0.298	-0.0674
	(0.926)	(0.439)	(0.417)		(0.456)	(0.244)
Front Ready	-1.757**	0.111	-0.724**	-0.303		0.189
	(0.842)	(0.434)	(0.347)	(0.287)		(0.286)
Front Drink	-1.639**	0.846**	-0.686**	-0.126	-0.628	
	(0.810)	(0.424)	(0.340)	(0.288)	(0.452)	
Constant	11.91***	4.009***	1.771*	0.594	0.967	0.0594
	(2.188)	(1.169)	(1.022)	(0.735)	(0.759)	(0.688)
Panel C: Nutrients per Food Basket	**Calories**	**Fat**	**Sat Fat**	**Carbs**	**Sugar**	**Protein**
Front Fruit	1135.3*	-30.08	-8.573	342.6***	16.00	-6.022
	(620.7)	(24.42)	(10.30)	(130.9)	(56.03)	(38.69)
Front Meat	1249.1**	-10.60	-3.043	313.2***	61.23	12.78
	(562.6)	(20.46)	(8.557)	(109.3)	(51.27)	(33.41)
Front Bread	1844.3***	5.101	3.333	463.1***	150.5***	-19.51
	(521.5)	(23.24)	(9.861)	(100.5)	(49.80)	(32.53)
Front Conf	1267.8**	20.59	12.74	216.8*	-20.55	50.44
	(623.5)	(21.78)	(9.088)	(118.9)	(52.88)	(32.53)
Front Ready	303.8	-17.90	-0.505	161.5	56.70	-39.92
	(669.6)	(23.69)	(10.07)	(125.2)	(56.34)	(37.69)
Constant	9052.1***	243.1***	64.67**	1130.5***	743.6***	490.8***
	(1681.9)	(60.21)	(26.11)	(342.8)	(153.9)	(86.00)
Controls	Y	Y	Y	Y	Y	Y
Observations	255	255	255	255	255	255

Note: Robust standard errors in parentheses. Asterisks (***), (**) and (*) denote variables significant at 1%, 5% and 10% levels respectively. This table reports the results from our linear regression estimates of equation 2. Panel A regresses total expenditure on each food and drink category (in £) on a series of dummy variables denoting which category the subjects were initially exposed to upon accessing the food choice tool. In Panel B a similar regression is carried out, only this time our dependent variable in each column is the total number of items per category selected by each subject. Note that in both Panels A and B the omitted category in each column corresponds to the category used as the dependent variable, in order to facilitate the interpretation of results. For example, in Panel A, Column 1, since our dependent variable is total expenditure on fruit and vegetables, the omitted (dummy) initial category is also fruit and vegetables. In Panel C we also perform a similar regression, although in this case the dependent variable is the aggregate value of one of the six nutrients captured by our food choice tool. In this case, the omitted category across each of the six columns is the drinks category. In Panels A to C we also include a number of control variables in our regression models (listed in Appendix IV).

Appendices

Appendix I: Copy of Food Frequency Questionnaire

These questions are about food and drink you consumed during the past month, that is, the past 30 days. When answering, please include meals and snacks at home, at work, in restaurants, or anywhere else.

Please enter your username

Please enter your desk number

Please tick how often you ate at least ONE portion of the following foods and drinks over the past month (a portion includes a handful of grapes, an orange, a serving of carrots, a side salad, a slice of bread, a glass of liquid).

	Rarely or Never	Less than 1 a Week	Once a week	2-3 times a week	4-6 times a week	1-2 times a day	3-4 times a day	5+ a day
Fruit (tinned/fresh)	○	○	○	○	○	○	○	○
Fruit juice (not cordial or squash)	○	○	○	○	○	○	○	○
Salad (not garnish added to sandwiches)	○	○	○	○	○	○	○	○
Vegetables (tinned / frozen / fresh but not potatoes	○	○	○	○	○	○	○	○
Chips / fried potatoes	○	○	○	○	○	○	○	○
White rice or potatoes								

like baked, boiled, mashed or sweet potatoes	O	O	O	O	O	O	O	O
Beans or pulses like baked beans, lentils, chick peas, dahl	O	O	O	O	O	O	O	O
Tea or coffee sweetened with sugar or honey, including iced tea and frappuccino	O	O	O	O	O	O	O	O

Please tick how often you ate at least ONE portion of the following foods and drinks over the past month (a portion includes a 30g bowl of cereal, 25g of cheese, a packet of crisps, 2 biscuits, a slice of bread, a glass of liquid).

	Rarely or Never	Less than 1 a Week	Once a week	2-3 times a week	4-6 times a week	1-2 times a day	3-4 times a day	5+ a day
Fibre-rich breakfast cereal like Weetabix, Fruit 'n Fibre, Porridge, Muesli	O	O	O	O	O	O	O	O
Wholemeal bread or chapattis	O	O	O	O	O	O	O	O
Brown rice / bulgur wheat / quinoa	O	O	O	O	O	O	O	O
Cheese / yoghurt	O	O	O	O	O	O	O	O
Crisps / savoury snacks	O	O	O	O	O	O	O	O
Sweet biscuits, cakes, chocolate, sweets	O	O	O	O	O	O	O	O
Ice cream / cream	O	O	O	O	O	O	O	O
Non alcoholic fizzy drinks / pop (not sugar free or diet)	O	O	O	O	O	O	O	O

Please tick how often you ate at least ONE portion of the following foods and drinks over the past month.

	Rarely or Never	Less than 1 a Week	Once a week	2-3 times a week	4-6 times a week	At least everyday
Beef, Lamb, Pork, Ham - steaks, roasts, joints,	O	O	O	O	O	O

mince or chops						
Chicken or Turkey - steaks, roasts, joints, mince or portions (not in batter or breadcrumbs)	○	○	○	○	○	○
Sausages, bacon, corned beef, meat pies/pasties, burgers	○	○	○	○	○	○
Chicken/turkey nuggets. turkey burgers, chicken pies, or in batter or breadcrumbs	○	○	○	○	○	○
White fish in batter or breadcrumbs - like fish 'n chips	○	○	○	○	○	○
White fish not in batter or breadcrumbs	○	○	○	○	○	○
Oily fish - like herrings, trout, salmon, sardines, mackerel, fresh tuna (not tinned tuna)	○	○	○	○	○	○

What milk do you USUALLY use or drink, such as in hot & cold drinks or on cereal (including tea, coffee, hot milk, milkshakes, or on cereal)

Whole / full-fat milk

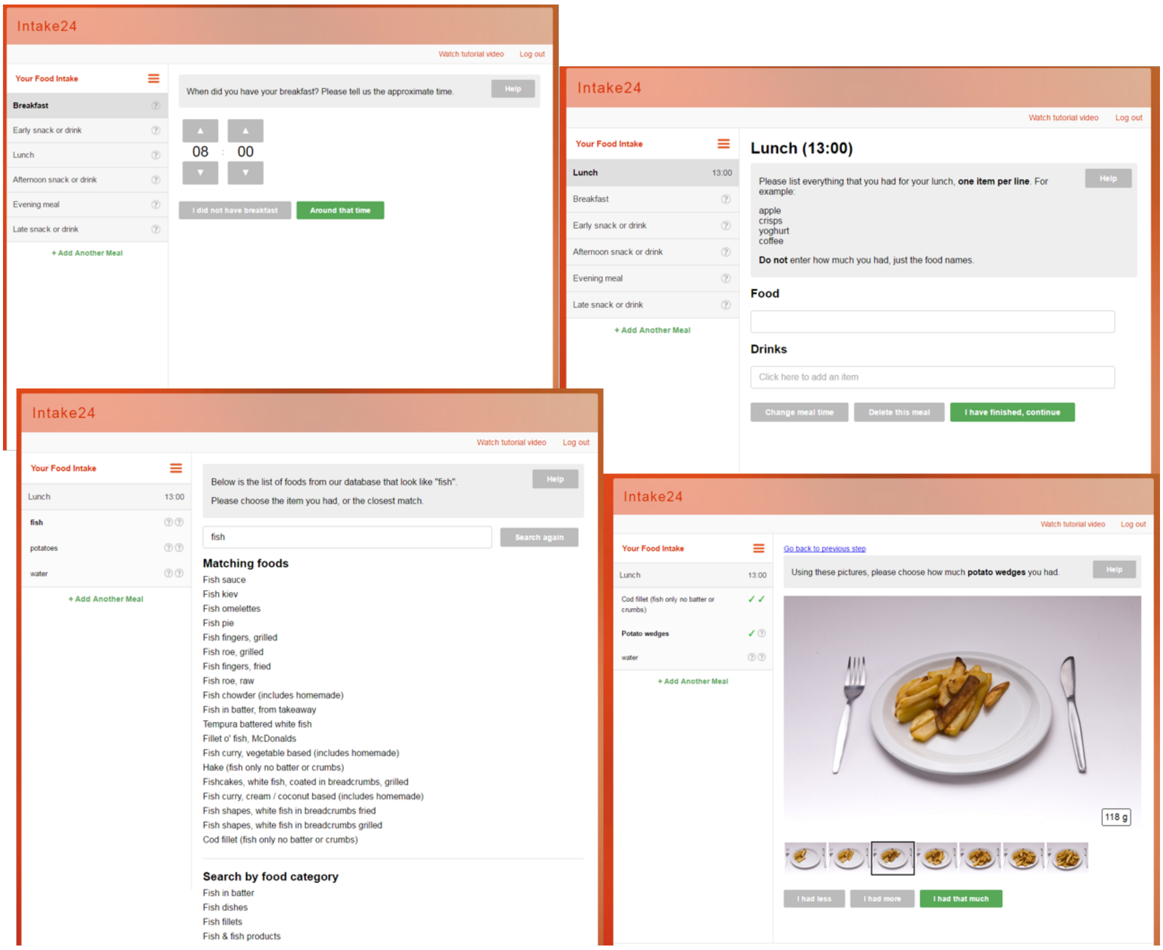
Semi-skimmed milk

Skimmed Milk

Rarely / never use milk

Other (please specify)

Appendix II: Screenshot of 24-Hour Dietary Recall (INTAKE24)



Appendix III: Food and Drink Items used in Food Frequency Questionnaire Nutrient Calculations

Category	**Item**
Fruit	Royal Gala Apples
Fruit	Fairtrade Bananas
Fruit	Easy Peeler Oranges
Fruit	Red Seedless Grapes
Fruit	Conference Pears
Fruit	Raspberries
Fruit	Strawberries
Fruit	Peaches
Fruit	Kiwi Fruit
Fruit juice	Smooth Orange Juice, Not from Concentrate
Fruit juice	Smooth Orange Juice, from Concentrate
Fruit juice	Pressed Apple Juice, Not from Concentrate
Fruit juice	Apple Juice, From Concentrate
Fruit juice	Orange Juice with Bits, Not From Concentrate
Fruit juice	Apple and Mango Juice, Not from Concentrate
Fruit juice	Mango and Passion Fruit Smoothie
Fruit juice	Strawberry and Banana Smoothie
Salad	Bistro Salad
Salad	Italian Style Salad
Salad	Mixed Leaf Salad
Salad	Sweet Leaf Salad
Salad	Babyleaf Salad
Salad	Crispy Salad
Vegetables	Cherry Tomatoes
Vegetables	Closed Cup White Mushrooms
Vegetables	Mixed Peppers
Vegetables	Carrots
Vegetables	Onions
Vegetables	Fine Beans
Vegetables	Broccoli
Vegetables	Sweetcorn
Vegetables	Cucumber
Vegetables	Red Onions
Chips/fried potatoes	Homestyle Chips
Chips/fried potatoes	Straight Cut Chips
Chips/fried potatoes	French Fries
Chips/fried potatoes	Oven Chips
White rice or potatoes	Baked Potatoes
White rice or potatoes	Maris Piper Potatoes
White rice or potatoes	Baby Potatoes
White rice or potatoes	Sweet Potatoes
White rice or potatoes	Mashed Potatoes
White rice or potatoes	Basmati Rice
White rice or potatoes	Arborio Rice
Beans or pulses	Baked Beans
Beans or pulses	Baked Beans in Tomato Sauce
Beans or pulses	Green Lentils
Beans or pulses	Red Lentils
Beans or pulses	Chickpeas

Category	Item
Tea or coffee sweetened	Tea
Tea or coffee sweetened	Capuccino
Tea or coffee sweetened	Barista Coffee
Fibre-rich breakfast cereal	Weetabix
Fibre-rich breakfast cereal	Fruit and Fibre
Fibre-rich breakfast cereal	Porridge
Fibre-rich breakfast cereal	Muesli
Wholemeal bread or chapattis	Wholemeal Bread
Brown rice/bulgur wheat/quinoa	Brown Basmati Rice
Brown rice/bulgur wheat/quinoa	Quinoa
Brown rice/bulgur wheat/quinoa	Bulgur Wheat
Cheese/yoghurt	Mature Cheddar
Cheese/yoghurt	Red Leicester
Cheese/yoghurt	Greek Style Yoghurt
Cheese/yoghurt	Natural Yoghurt
Crisps/savoury snacks	Tortilla Crisps
Crisps/savoury snacks	Cheese and Onion Crisps
Crisps/savoury snacks	Salted Crisps
Crisps/savoury snacks	Cashews
Crisps/savoury snacks	Peanuts
Sweet biscuits, cakes, chocolate, sweets	Milk chocolate digestives
Sweet biscuits, cakes, chocolate, sweets	Rich Tea Biscuits
Sweet biscuits, cakes, chocolate, sweets	Shortbread
Sweet biscuits, cakes, chocolate, sweets	Pain au Chocolat
Sweet biscuits, cakes, chocolate, sweets	Chocolate Cake
Sweet biscuits, cakes, chocolate, sweets	Milk Chocolate Fingers
Sweet biscuits, cakes, chocolate, sweets	Chocolate Buttons
Sweet biscuits, cakes, chocolate, sweets	Fudge Chocolate Bar
Sweet biscuits, cakes, chocolate, sweets	Assorted Candy
Sweet biscuits, cakes, chocolate, sweets	Marshmallows
Ice cream/cream	Vanilla Ice Cream
Ice cream/cream	Ice Cream Cone
Ice cream/cream	Whipped Cream
Non alcoholic sugary fizzy drinks/pop	Cola
Non alcoholic sugary fizzy drinks/pop	Lemonade
Non alcoholic sugary fizzy drinks/pop	Orange Ade
Non alcoholic sugary fizzy drinks/pop	Irn Bru
Beef, lamb, pork, ham	Beef Mince
Beef, lamb, pork, ham	Honey Roast Ham
Beef, lamb, pork, ham	Beef Joint
Beef, lamb, pork, ham	Beef Steak
Beef, lamb, pork, ham	Gammon Joint
Beef, lamb, pork, ham	Pork Loin
Beef, lamb, pork, ham	Pork Chops
Beef, lamb, pork, ham	Lamb Mince
Beef, lamb, pork, ham	Lamb Leg
Beef, lamb, pork, ham	Lamb Chops
Chicken or turkey	Chicken Breats Fillets
Chicken or turkey	Chicken Thigh Fillets
Chicken or turkey	Whole Chicken
Chicken or turkey	Turkey Mince
Chicken or turkey	Turkey Breast Steaks
Chicken or turkey	Turkey Breast Fillets
Sausages, bacon, meat pies, burgers	Unsmoked Bacon
Sausages, bacon, meat pies, burgers	Pork Sausages
Sausages, bacon, meat pies, burgers	Smoked Bacon
Sausages, bacon, meat pies, burgers	Cumberland Sausages
Sausages, bacon, meat pies, burgers	Beef Burgers
Sausages, bacon, meat pies, burgers	Beef Meatballs

Category	Item
Sausages, bacon, meat pies, burgers	Pork Pie
Sausages, bacon, meat pies, burgers	Steak Pie
Chicken/turkey nuggets, burgers, pies	Chicken Kiev Garlic
Chicken/turkey nuggets, burgers, pies	Chicken Kiev Ham
Chicken/turkey nuggets, burgers, pies	Chicken Nuggets
Chicken/turkey nuggets, burgers, pies	Chicken Pie
Chicken/turkey nuggets, burgers, pies	Turkey Escalope
White fish in batter or breadcrumbs	Haddock Fishcakes
White fish in batter or breadcrumbs	Breaded Cod
White fish in batter or breadcrumbs	Cod Fishcakes
White fish in batter or breadcrumbs	Dusted Lemon Sole
White fish not in batter or breadcrumbs	Cod Fillets
White fish not in batter or breadcrumbs	Sea Bass Fillets
White fish not in batter or breadcrumbs	Basa Fillets
White fish not in batter or breadcrumbs	Plaice Fillets
Oily fish (not tinned)	Salmon Fillet
Oily fish (not tinned)	Smoked Salmon Fillet
Oily fish (not tinned)	Trout Fillet
Oily fish (not tinned)	Mackerel Fillets

Category	Calories	Fat	Sat Fat	Carbohydrates	Sugar	Protein
Fruit (tinned/fresh)	49.444	0.433	0.089	10.944	10.578	0.878
Fruit juice	44.750	4.688	3.938	9.925	8.900	0.538
Salad	20.667	0.467	0.100	1.733	1.283	1.717
Vegetables	45.100	0.630	0.100	4.630	3.310	1.630
Chips/fried potatoes	199.500	5.975	0.725	32.400	0.500	2.925
White rice or potatoes	109.714	1.157	0.457	21.886	3.443	2.429
Beans or pulses	89.000	0.720	0.140	12.400	2.200	5.920
Tea or coffee sweetened	19.333	0.433	0.367	3.167	3.633	0.567
Fibre-rich breakfast cereal	369.750	5.100	1.425	66.000	11.975	10.650
Wholemeal bread or chapattis	221.000	1.800	0.400	37.800	4.100	10.000
Brown rice/bulgur wheat/quinoa	112.000	1.800	0.500	19.033	0.400	3.700
Cheese/yoghurt	245.500	19.350	12.575	3.200	3.150	14.925
Crisps/savoury snacks	555.000	38.520	5.080	36.720	3.500	13.160
Sweet biscuits, cakes, chocolate, sweets	445.700	18.310	9.510	63.990	41.010	5.440
Ice cream/cream	284.333	19.467	14.233	24.100	17.767	2.667
Non alcoholic sugary fizzy drinks	35.250	0.000	0.000	8.600	8.600	0.000
Beef, lamb, pork, ham	218.700	12.260	5.230	0.970	0.590	26.200
Chicken or turkey	161.500	4.117	1.083	0.500	0.500	30.583
Sausages, bacon, meat pies, burgers	244.375	14.663	5.638	9.075	1.350	18.550
Chicken/turkey nuggets, burgers, pies	262.400	15.480	3.980	17.040	1.260	13.140
White fish in batter or breadcrumbs	191.500	8.475	1.625	15.175	1.025	13.100
White fish not in batter or breadcrumbs	129.000	4.200	1.025	0.500	0.500	22.625
Oily fish (not tinned)	217.500	14.550	3.075	0.675	0.500	21.150

Appendix IV: List of Control Variables

Variable Name	Description of Variable
Male	Dummy denoting whether subject is male or not
Age	Variable denoting the subject's stated age
Employed	Dummy denoting whether subject is currently gainfully-occupied
Unemployed	Dummy denoting whether subject is currently unemployed and seeking work
Student	Dummy denoting whether subject is currently a full-time student
Postgrad	Dummy denoting whether subject's highest level of education is a post-graduate degree
Undergrad	Dummy denoting whether subject's highest level of education is an under-graduate degree
A-level	Dummy denoting whether subject's highest level of education is an A-level certificate (or equivalent)
Income > £25000	Dummy denoting whether subject's annual household income is above £25,000
Income £20000-£25000	Dummy denoting whether subject's annual household income is between £20,000 and £25,000
Income £15000-£20000	Dummy denoting whether subject's annual household income is between £15,000 and £20,000
Income £10000-£15000	Dummy denoting whether subject's annual household income is between £10,000 and £15,000
Income £5000-£10000	Dummy denoting whether subject's annual household income is between £5,000 and £10,000
White	Dummy denoting whether subject's race is Caucasian
Married	Dummy denoting whether subject is currently married
Blood Sugar	Dummy denoting whether subject has never been told that s/he has high blood pressure
Time 9.30am	Dummy denoting whether subject attended a 9:30am experimental session
Time 11.30am	Dummy denoting whether subject attended an 11:30am experimental session
Time 2.30pm	Dummy denoting whether subject attended a 2.30pm experimental session
Mon	Dummy denoting whether subject's experimental session was on Monday
Tues	Dummy denoting whether subject's experimental session was on Tuesday
Wed	Dummy denoting whether subject's experimental session was on Wednesday

Variable Name	Description of Variable
Thurs	Dummy denoting whether subject's experimental session was on Thursday